Evaluating Electrograms Domain Knowledge for Enhancing Catheter Ablation Outcomes Based on Time Series Features

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Abstract

Objective: Ablation of persistent atrial fibrillation (persAF) targets based on signal processing techniques (complex fractionated atrial fibrillation (CFAE), dominant frequency (DF) and re-entries (rotors)) have been disappointing. Machine learning tools may be the solution to improve the catheter ablation responses using intracardiac electrograms (EGMs) collected by non-contact techniques using features from three signal domains (spectral, temporal and statistical). Methods: 3206 EGMs were collected from 10 patients undergoing a catheter ablation for the first time. 1716 EGMs have a negative catheter ablation response and 1490 EGMs a positive response. A Logistic Regression (LR) classifier based on time series features was used to classify the EGMs based on positive (AF termination or AFCL≥10ms) and negative responses (AFCL unchanged or decreased by <10ms) to catheter ablation. The performance of LR classifier for each domain features was evaluated using five different matrices (validation accuracy, sensitivity, specificity, precision and F1_score). Results: A cross validation accuracy of 91.64%, 72.68% and 67.34% was achieved using LR classifier based on spectral, temporal and statistical features, respectively. The four remaining evaluation techniques ranged between (90%-92%) for spectral features, (66%-78%) for temporal features, and from 64% to 69% for statistical features. Conclusion: The highest performance was obtained with spectral features, followed by temporal features, whereas statistical features achieved the lowest scores. Hence, it can be concluded that spectral characteristics of EGMs are the most important to classify and predict the catheter ablation responses.

1. Introduction

Atrial fibrillation is the most common abnormal heart rate (arrhythmia) and it corresponds to an increased risk of stroke and death-rate of five and two folds, respectively [1]. There are several tools that have been used to treat the AF. Catheter ablation is an efficient tool for treating AF in the early-stage paroxysmal AF, but it is less effective for the advanced stages of persistent AF (persAF). Several signal processing techniques based on different EGM signal domains have been used to guide a catheter ablation for AF therapy such as DF, OI and RI as features from the EGM spectral domain [2, 3]; mean, median as features from the statistical domain [4], and entropy [5] as a feature from the temporal domain. All of the mentioned techniques above have failed to produce good treatment outcomes due to multiple mechanisms that are responsible for initiation and maintenance of AF such as a fast discharging automatic ectopic foci activity; single re-entry activity; multiple wavelets activity; and the functional re-entries activates resulting from rotors [6]. Machine learning tools have been used in several biomedical applications and are good tools for finding patterns from high dimensional data [7]. Therefore, these tools may be a good approach to treat persAF by enhancing the catheter ablation to burn sites (nodes) that give a positive outcome for AF therapy.

In the current work, features from three EGM signal domains were used to investigate and evaluate the EGM signal domains for positive ablation. EGMs positive and negative responses to catheter ablation were used as two categories to identify the outcomes of ablation procedure to EGMs sites (nodes in non-contact mapping catheter) using the features from three EGM signal domains. AF termination, increasing of AF cycle length (AFCL), deceasing in AFCL [8] and AFCL not changing were used as a ground truth for EGMs dataset.

2. Material and Methods

2.1. Dataset

The dataset was collected from 10 persistent AF patients undergoing first time left atrial catheter ablation. The collection of data was done using non-contact mapping catheter using (Ensite array – St. Jude Medical) system from the high dominant frequency (HDF) regions in the left atrium. These regions were identified as described before [9]. The data were exported to a

MATLAB environment to guide the ablation procedure. The dataset was collected before and after ablation (pre- and post-ablation) from all ten patients. Four out of ten patients had AF termination (1 sinus rhythm and 3 flutter) before pulmonary vein isolation (PVI). Pre-ablation of EGMs were recorded and exported off line up to 20 seconds duration time for training and testing the 10 patients. AFCL pre- and post-ablation for each of the DF atrial sites were recorded using "LabsystemTM Pro EP Recording System". The data were classified into two classes as labels: (i) positive response to ablation (AF terminated or AFCL increased (≥10ms)), and (ii) negative response to ablation (AFCL decreased (<10ms) or not changed) [8]. The dataset was labelled and approved by an interventional cardiologist at Leicester Glenfield Hospital.

2.2. Research Toolkit

Time Series Feature Extraction Library (TSFEL) is one of the most powerful and efficient available tool libraries embedded in python environment. This library is used to compute, extract and evaluate a variety of handcrafted features and knowledge domain features from biomedical signals. The library can compute more than 390 features (table 1) based on three processing signal domains (spectral, temporal and statistical) [10].

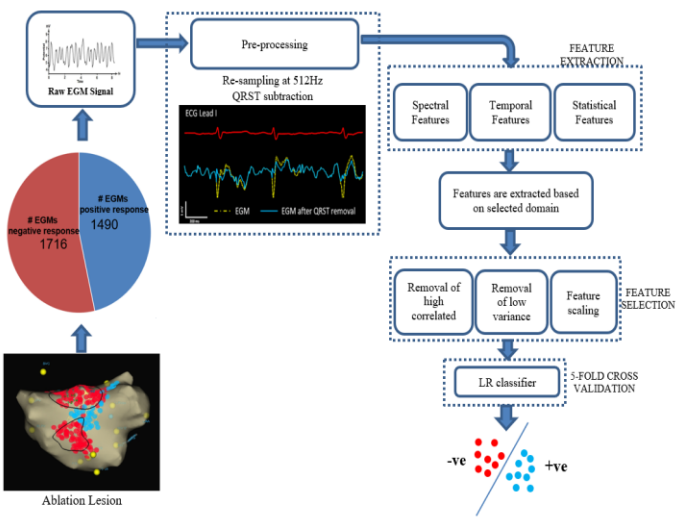


Figure 1. The complete diagram of the proposed method

2.3. Pre-Processing

Twenty seconds-long EGMs were sampled at 2034.5Hz and these were resampled at 512 Hz using cubic interpolation method to reduce the data storage and further processing time. QRST subtraction was performed to remove the ventricular far-field activity from each EGM [11]. The middle window of Figure 1 shows the process of QRST subtraction.

2.4. Feature Extraction

TSFEL has been used as a powerful tool to extract features from biomedical signals. This package provides the support for fast exploratory data analysis for multidimensional time series data. The features that are extracted by this library from each EGMs are described in table1.

Table 1. Features extracted based on bio signal domain [10]

Spectral Domain	Temporal Domain	Statistical Domain
• FFT Mean Coefficients (#256) • Fundamental Frequency • Human Range Energy • LPCC (#13) • Maximum Frequency • Maximum Power Spectrum • Median Frequency • MEL Frequency Cepstral Coefficients (#12) • Power Bandwidth • Spectral Centroid • Spectral Decrease • Spectral Distance • Spectral Entropy • Spectral Kurtosis • Spectral Positive turning points • Spectral Roll-off • Spectral Roll-On • Spectral Skewness • Spectral Slope • Spectral Spread • Spectral Variation • Wavelet Absolute Mean (#9) • Wavelet Energy (#9) • Wavelet Entropy • Wavelet Standard Deviation (#9) • Wavelet Variance (#9)	• Absolute energy • Area Under the Curve • Autocorrelation • Centroid • Entropy • Negative turning points • Mean Absolute Difference • Mean differences • Median Absolute Difference • Median Difference • Positive turning points • Peak to Peak Distance • Signal Distance • Slope • Sum Absolute Difference • Total energy • Zero Crossing Rate • Neighborhood peaks	• ECDF (#10) • ECDF Percentile (#2) • ECDF Percentile Count (#2) • Histogram (#10) • Interquartile Range • Kurtosis • Maximum • Mean • Mean Absolute Deviation • Median • Median Absolute Deviation • Minimum • Root Mean Square • Skewness • Standard Deviation • Variance
# features = 336	**#features = 18**	**#features = 36**
# Total =390		

2.5. Feature Selection

The role of feature selection in optimizing the classification using machine learning classifiers is undeniable. The better performance for machine learning classifiers for prediction of unseen data can be done by using an optimum feature selection [12]. Hence, an efficient implementation of ML classifiers is based on selecting the best features as inputs for ML training.

2.5.1 Removal of High Correlated Features

The criteria that have been applied to remove high correlated features in this approach is based on Pearson's correlation. [13]. In this work, features that have a correlation greater than 0.95 have been removed from the features list.

2.5.2. Removal of Low Variance Features

Features with less than the specific threshold were removed from the feature list. A zero has been selected as a threshold value in the proposed method; this value is kept all features with non-zero variance [14].

2.5.3. Features Scaling

The scaling method is used to normalize the range of independent features of data. It is observed that the value of features that have large magnitude tend to dominate the prediction towards a particular class. There are many types of scaling methods, but the one that has been used in this work is called standardization. Standardization operation rescales data to have a mean (μ) of 0 and standard deviation (σ) of 1 (unit variance). The standard score (s) to which the value of feature is to be scaled is given by finding the value of mean (μ) and the standard deviation (σ) as in the following formula:

$$s = \frac{x - \mu}{\sigma} \tag{1}$$

where

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{2}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{3}$$

Here, x denotes to the selected feature, μ stands for the mean, and σ represents the standard deviation of the feature.

3. Experimental Results and Discussion

The LR classifier was trained and validated on the dataset mentioned in section 2.1 above. To evaluate the performance of LR classifier for three EGM signal domain features, several evaluation metrics have been chosen that are recommended by AAMI [15]. Five-fold cross-validation technique was used for training and validating, 80% and 20% of dataset were used for training and validating, respectively. Following the results from bar chart (Figure 2), it can be seen that the proposed approach can perform almost 91.64%, 72.68% and 67.34% overall accuracy for spectral, temporal and statistical domain, respectively. The proposed method shows a sensitivity of 91.07%, 66.91% and 66.04%; specificity of 92.13%, 77.68% and 68.47%; precision of 90.95%, 72.25% and 64.52%; F1_score of 91.01%, 69.48% and 65.27% for spectral, temporal and statistical domain, respectively. The confusion matrices (CMs) for the three classifiers are shown in Figure 3. The CMs show the number of TP, TN, FP and FN values of EGMs classification using three signal domains. Figure 4 illustrates the receiver operating characteristic curve (ROC) for the positive and negative classes: AUC = 0.76, 0.81 and 0.96 for statistical, temporal and spectral features. Grid Search technique has been used to optimize the hyperparameters during the simulation. Hence, the hyperparameters that have been set using this LR classifier:

- C = 1, 8 and 9 for statistical, temporal and spectral domain features, respectively. It is the inverse of regularization strength, where the smaller values of C represent a stronger regularization.
- Max_iter = 100 for the three features domain (it is the maximum number of iterations that makes the classifier solver to coverage)
- Penalty = L2 (it applies the regularization to the LR algorithm during the training process).
- Solver = ‘lbfgs’ for statistical and temporal domain features classifier and ‘liblinear’ for spectral domain features classifier (An algorithm that used in the optimization problem).

It can be noticed that the EGM spectral domain features have more contribution on successful ablation than other two domains. These results support the findings, the spectral analysis of EGMs play a significant role to target the sites of AF driver for successful ablation and in particular the DF, which has been widely used as a feature to analyze the atrial EGM [2]. DF is the frequency with the maximum amplitude in EGM signal, and can be evaluated using Fast Fourier transform (FFT). FFT mean coefficients (power spectral density, 256 features) represented the majority features extracted using this library. Time domain features have been used to target the AF drivers such as entropy [16], mean and median of differences and these features have resulted the mediocre performance. EGM features from the statistical signal domain have resulted the lowest performance, due to few features from this domain have been used as descriptors to target the AF driver such as a mean voltage [4] of EGMs and the standard deviation (STD).

4. Conclusions

The proposed approach has been used to classify and identify the responses of EGMs to catheter ablation for an efficient AF treatment. Features from three EGM signal domains were applied separately as inputs to LR classifier. Classifier performance was measured for each feature domain. Experimental simulations show that the proposed approach can perform with 91.64%, 72.68% and 67.34% overall accuracy for spectral, temporal and statistical domain, respectively. The proposed method shows a sensitivity of 91.07%, 66.91% and 66.04%; specificity of 92.13%, 77.68% and 68.47%; precision of 90.95%, 72.25% and 64.52%; F1_score of 91.01%, 69.48% and 65.27% for spectral, temporal and statistical domain, respectively. From the obtained results, it can be concluded that the highest performance was from the features that are extracted from spectral domain, statistical features have achieved the lowest performance, with temporal features in between those.

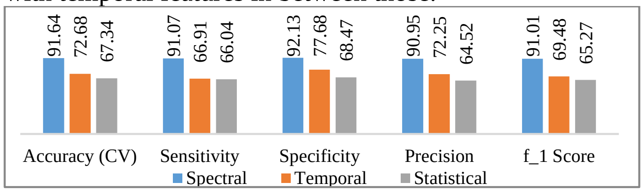
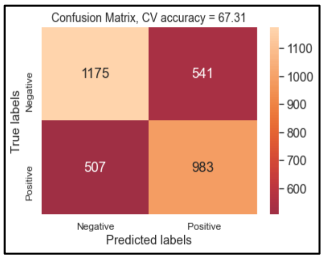
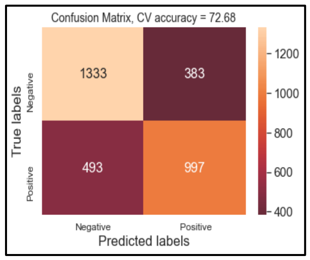


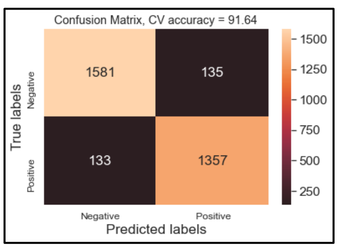
Figure 2. Performance of LR for features from 3 domains



(a)

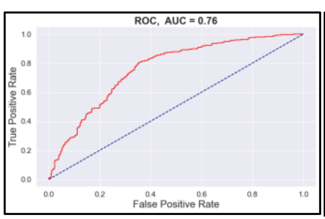


(b)

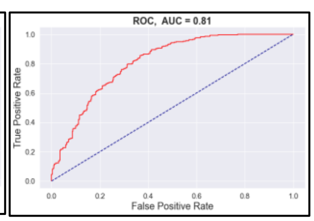


(c)

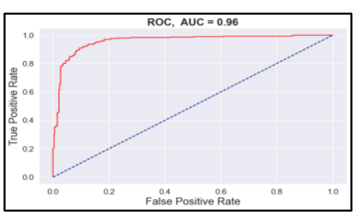
Figure 3. CM of (a) statistical (b) temporal and (c) spectral features



(a)



(b)



(c)

Figure 4. ROC and AUC of LR classifier for (a) statistical, (b) temporal and (c) spectral features

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